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A Predictive Framework for Solar Energy Generation Using Artificial Intelligence

Aims of The Study

1. To Highlight current challenges and potential improvements.
2. To Review existing machine learning models and techniques for deploying the reliable predictive model
3. To Identify the significance of various parameters affecting the performance of solar power generation.
4. To Develop reliable Predictive Model using Artificial Intelligence
5. To Validate the developed system in real-world scenario.

Objectives of Study

1. To implement and evaluate various machine learning models for solar power Prediction.
2. To develop an accurate and reliable solar power prediction model using Historical solar and weather data.
3. To explore and evaluate significance of parameters that influence the prediction.
4. To apply the predictive model on different data sets for performance evaluation.
5. To validate the developed model for its performance accuracy on real-time data.

Study Background (Literature Review) and significance of study

Introduction

Solar energy, while advantageous, poses challenges due to its variability and intermittency. The integration of solar power into the grid requires addressing these fluctuations. Solar power forecasting is crucial for grid stability and reliable power supply:

Accurate forecasts enable grid operators to anticipate solar generation fluctuations.

Precise forecasts optimize solar energy use and manage conventional backup sources efficiently.

Forecasting contributes to grid stability, reduced fossil fuel backup generation, and lower operational costs.

The Motivation for the research includes the following key points:

- Solar power prediction models are essential for transitioning to low-carbon energy futures.
- Advancements in forecasting technologies with AI and machine learning, have improved/enhanced the accuracy of solar power prediction.

The general steps involved in the solar power prediction model include:

- Stages such as data preprocessing, feature selection, model training, evaluation, and visualization.
- Preprocessing techniques and feature selection methodologies enhance model performance and streamline forecasting.
- AI models like LSTM, RNN, ANN, SVM, Random Forest, and Gradient Boosting capture complex patterns in solar energy data effectively.
- Training AI models on historical data helps identify trends and correlations in solar power generation.
- Model evaluation using metrics like MSE and RMSE ensures Prediction accuracy.
- Visualizing forecast results aids stakeholders in understanding forecast reliability and areas for enhancement.

In summary, the optimization of solar power prediction by integrating with Artificial Intelligence can be achieved for renewable energy usage and grid management, paving the way for a sustainable future powered by solar energy.

Literature Review

In Recent research, Several studies have applied various machine leaning algorithm to predict solar energy output. For instance, Uddin, Nur, Edi Purwanto, and Hari Nugraha.(2024) used algorithm with which 69.6% accuacary is achieved where further improvement in accuracy can be expected with the help of advance machine learning algorithm x, similarly, Ponraj, Ram Prakash, et al (2023) uses DT and RF algorithm where RMS and R2values of Random Forest algorithm are minimum compared to DT algorithm however, model may face trouble by problem like overfitting, computational complexity since relatively small dataset used. Sekar, S., et al (2023) have used SVM and also got accuracy of 98.%.where along with SVM different advance machine learning may also give better results. Gomathi, S., et al(2024), have used hybrid model random Forest and Artificial neural network enebles increased flexibility in designed model but thiese Predictive models rely heavily on historical data, Zhang, Xinmin, et al(2019), Clustering and blending strategies are applied which results in significant reduction in normalized RMSE by 13.80% to 61.21% compared to three baseline methods yet show significant scope of Extension to Probabilistic Forecasts,

In Olcay, Kadir, Samet Giray Tunca, and Mustafa Arif Özgür(2024), Random Forest and LSTM algorithms are used and it is seen that LSTM artificial neural networks perform much better than the RF model, In paper, Jafarzadeh, Saeed, M. Sami Fadali, and Cansın Yaman Evrenosoglu (2012), have implemented Takagi–Sugeno–Kang (TSK) fuzzy model. Which may further focus on improving the representation of uncertainty in solar power predictions, Siddiqui, Raheel, et al.,(2020) both artificial neural network LM-ANN, GD-ANN have used showing a high degree of accuracy, with numerical error studies indicating a correspondence of 98-99%. Still finds potential for real-time applications in solar energy forecasting and optimization. Wang, Jianxiao, et al (2017), different machine learning models like PCA, KNN and SVM have been used here alongwith parameters from PV models which still scope

to explore the integration of real-time weather data or the impact of extreme weather events on solar power generation. Sharma, Neetan, et al (2023):, have used methods like GD and LM ANN for diverse weather prediction however Developed model may struggle Forecasting errors due to environmental factors affecting solar power supply.

Kim, Seul-Gi, Jae-Yoon Jung, and Min Kyu Sim(2019), machine learning lagorithms like KNN, SVR, ANN, RFR are used however Radiation was the most significant variable, contributing 43.7% to the prediction performance, overall it lacks in applicability to diverse geographical locations and other renewable energy sources. López Gómez, Javier, et al. (2022) uses ANN algorithm, itwhere finds research gap like Lack of generalizability. Satkunam, Pankajan (2024), LSTM algorithm was used still it has scope to include more weather conditions like cloud presence and solar panel location factors like dust, dirt, and pollution. Zhang, Yue, et al.(2022), It combines long-short-term-memory networks and autoencoders to address the inherent variability in PV generation due to uncertain weather conditions, Andrade, José R., and Ricardo J. Bessa (2017), It combines the gradient boosting trees algorithm with feature engg. techniques that extract the max.info from the NWP grid, Average point forecast improvement (in terms of mean absolute error) of 16.09% and 12.85% for solar and wind power, respectively.

Lo Hsin-Yen, et al. (2025),have used CNN + quantile regression (QR) machine learning technique, this study provides a practical and scalable solution for reliable solar power forecasting balancing accuracy and computational efficiency however there is lack of efficient and accurate probabilistic forecasting methods that address both computational complexity and variability in data. Mei, Fei, et al.(2020), LSTM-QRA-based nonparametric methos has been used. LSTM-QRA effectively integrates deterministic models for nonparametric probabilistic forecasting Input feature selection needs improvement and optimization. however Input feature selection needs improvement and optimization. Sari, Dian Puspa, Ahmad Zainul Fanani, and Guruh Fajar Shidik.(2022), LSTM with ReLU activation for hourly solar radiation prediction It effectivelyutilizes LSTM to predict hourly solar radiation resulting in MSE of 0.1885. large datasets may be useful to make predictions more accurately. Lyu, Cheng, and Sara Eftekharnejad (2024), proposes model which enhances forecasting accuracy and robustness, particularly in rapidly changing weather situations when accurate forecasts are challenging. Sharkawy, A. N., et al(2023), three types of ANNs are utilized for solar PV power estimation and upscaling forecast. MLFFNN outperforms as it is achieving lowest MSE of 0.27533 and the lowest absolute approximation error of 0.2099 MWh, indicating its effectiveness in power estimation and upscaling forecast.

Li, Jianjing, Chenghui Zhang (2022), have used LSTM, wavelet decomposition, CNN techniques

By which it is obtaining an average accuracy of 93.75% and 93.12% in the 10 MW and 100 kW power plants. however it may face challenges like Overfitting challenge with daily weather changes. Long, Huan, et al. (2023) has Improved TrAdaBoost algorithm for boosting ensemble interval prediction. Which shows significant improvements in prediction quality, with an average CWC

improvement ratio of 71.90%. Phan, Quoc-Thang, et al. (2022) in this study, two-stage deep learning framework is developed by combining LSTM and CNN. Doubleday, Kate, et al. (2020) uses Bayesian model averaging (BMA) post-processing method, still question aries about its applicability to different geographical regions or varying weather conditions. Kim, Hyeonjin, and Duehee Lee. (2021)uses Probabilistic graphical model for solar power forecasting.

Kharazi, Somaieh, et al. (2023), uses a feedback loop to ensure consistency, (SVR, CNN, LSTM) in terms of accuracy (MAPE, RMSE, MAE). Yet Model can perform better by integrating more diverse data sources, such as satellite imagery, Jang, Han Seung, et al. (2016), this study uses SVM, More focussed on prediction of solar irradiance by observation of Cloud cover. Asghar, Rafiq, et al. 2024, with the help of deep learning, hybrid BiLSTM-CNN, K-means algorithm it is achieving an RMSE of 77.73, MAE of 41.32, and MAPE of 5.085. however achieving an RMSE of 77.73, MAE of 41.32, and MAPE of 5.085. Hossain, Mohammad Safayet, and Hisham Mahmood. (2020), K-means algorithm is used here which addresses the challenge of accurately forecasting photovoltaic (PV) power generation, which is influenced by various weather parameters. But There is no discussion on the scalability and applicability of the proposed machine learning models in real-world scenarios or different geographical locations, Lim, Su-Chang, et al. (2022), in this study hybrid CNN-LSTM model achieved a mean absolute percentage error (MAPE) of 4.58 on sunny days and 7.06 on cloudy days,

Zhang, Yue, et al (2019), in this study, Convolutional Self-Attention based Long Short-Term Memory (LSTM) Is used, which has Limited impact of previous days' PV outputs on model performance. Yu, Dukhwan, et al. (2020), uses Convolutional Self-Attention based Long Short-Term Memory (LSTM), Long-term dependency problem affects prediction performance Helmy, Muhammad Fareezy Fahmy M., et al (2024), SVM achieved MAE of 0.4264 and RMSE of 0.5772, It highlights SVM's reliability and effectiveness. Andrade, José R., and Ricardo J. Bessa. (2017), here Methodology combines gradient boosting trees with feature engineering from numerical weather predictions (NWP), Average point forecast improvement: 16.09% for solar and 12.85% for wind power. Nuño, Edgar, et al. (2018), Transformation-based methodology is used and results from the six regions are included

.

National Status

Use of renewable energy sources like solar and wind for sustainable growth, while gradually reducing dependenace on non renewable resources such as coal, oil and gas. The Indian economy has depicted a healthy expansion during the FY 2023-24, with the Total Primary Energy Supply (TPES) registering a growth of 7.8% over the past year and stood at 9,03,158 KToE(Kilo Tonnes of oil Equivalent).

India has a huge potential for generation of renewable energy which stands at 21,09,655 Megawatt as on 31-Mar-24. As on 30-06-2023, a capacity of 37,990 MW has been sanctioned in 12 states. The approved parks are at various stages of implementation.

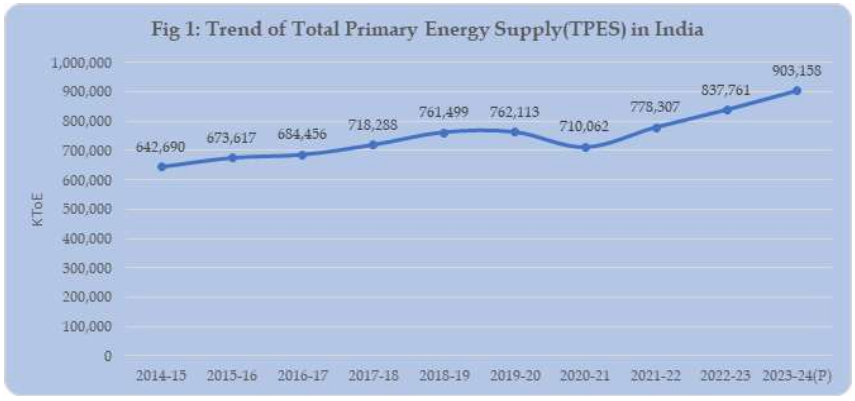

Fig. 1
Source adapted from [36]

Figure 1. shows the Trend of Total Primary Energy Supply (TPES) in India. In the trend from 2014-15energy supply of 642690KToE has increased to 903158 in the year of 2023-24.

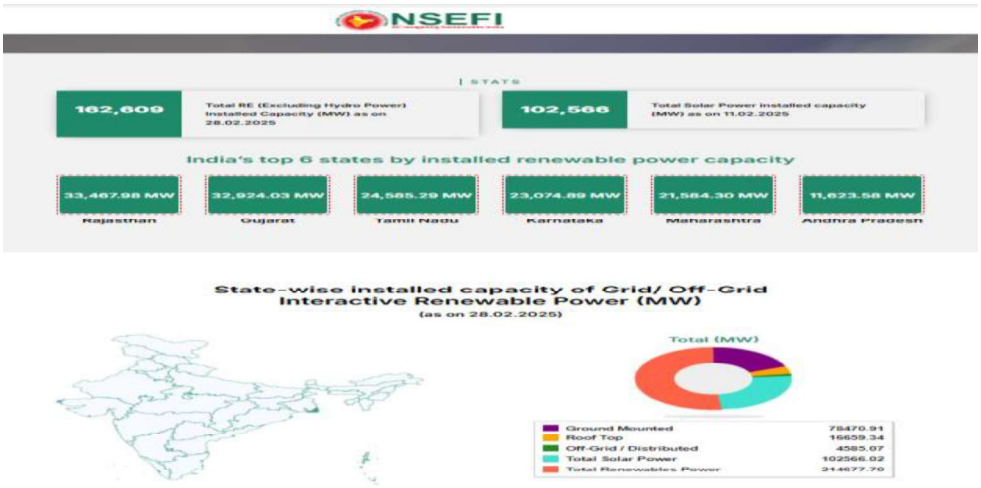

Fig.2
Source adapted from [37]

In figure 2., state wise installed capacity of Grid / Off- Grid interactive Renewable Power (MW) as on 28.02.25 has been shown by National Solar Energy Federation of India(NSEFI). Figure shows the installed renewable power capacity of top 6 states of India which are Rajasthan, Gujarat, Tamilnadu, Karnataka, Maharashtra and Andhra Pradesh.

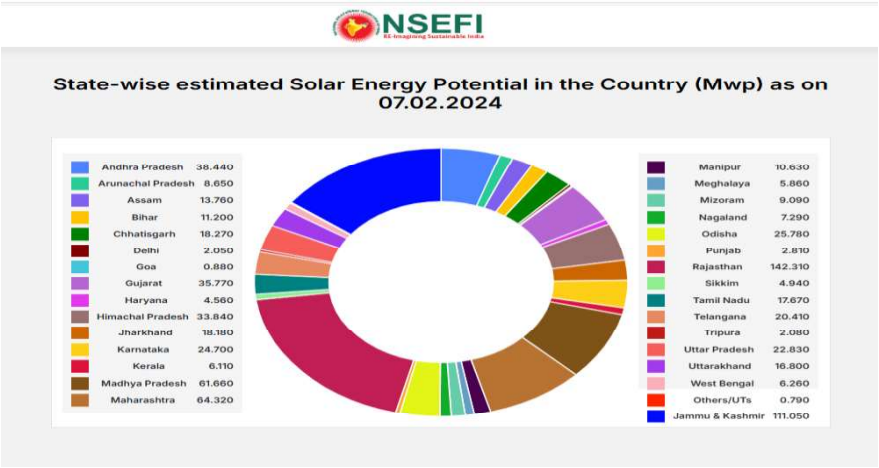

Fig.3
Source adapted from [38]
In figure 3. state wise iestimated Solar energy potential in the country (Mwp) as on 07.02.2024

International Status

Solar energy is prioritized because it is abundant renewable and central to reducing dependance on fossile fuels. India receives 5000 trillian kWh of solar radiation annually, far more than its currend power demamnd Solar energy now contributes 22% of India's installed capacity and is the largest share in renewables. Solar power produces zero greenhouse gas emissions during operation.

India is third largest solar power generator in 2023, india surpassed Japan to become the worlds third largest producer of solar electricity, a jump from ninth place in 2025.

Table.1 shows Top 20 Countries/Areas by Operating Solar Farm Capacity in Megawatts (MWac) published by Global Solar Power Tracker, February 2025. Summary data includes utility-scale solar farm phases 1 MW and greater.

Rank	Country/Area	Operating Capacity	Percent of Global Total
1	China	447,508	48.4%
2	United States	121,311	13.1%
3	India	72,300	7.8%
4	Japan	31,095	3.4%
5	Spain	28,014	3.0%
6	Germany	26,283	2.8%
7	Brazil	20,165	2.2%
8	Vietnam	12,902	1.4%
9	Mexico	12,787	1.4%
10	France	11,818	1.3%
11	Australia	11,626	1.3%
12	Chile	9,982	1.1%
13	United Kingdom	9,031	1.0%
14	South Korea	7,450	0.8%
15	United Arab Emirates	6,353	0.7%
16	Ukraine	5,259	0.6%
17	Italy	4,447	0.5%
18	Türkiye	4,077	0.4%
19	South Africa	3,992	0.4%
20	Netherlands	3,916	0.4%

Table.1
Source adapted from [38]

Study Hypothesis

Solar energy has emerged as one of the most promising reneqable sources due to its abundance, sustainability and its role in reducing dependence on fossil fuels.

- Application of AI framework can significantly improve the accuracy and reliability of prediction models and thereby contributing sustainable energy management.
- AI driven Model can minimize the solar power prediction error rates as compared to traditional

statistical or weather based methods.

- Use of parameters like solar irradiation, temperature, Humidity etc in the predictive framework enables the performance enhancement in prediction.

Study Rationale

- Renewable energy resources, particularly solar power, are essential for reducing greenhouse emissions and combating climate change.
- Accurate forecasting of solar power generation is crucial for improving the stability and quality of power grids.
- Various factors such as temperature, humidity, and cloud cover introduce uncertainties in solar power generation.

Research Methodology

Methodology plays an important role in achieving defined research objectives. Research methodology ensures structured framework for conducting study in a releable , systematic and scientific manner. It provides the results that can be applied to real world energy planning and management.

Weather Data Analysis:

For analysing weather data techniques such as time-series analysis, regression models may be used.

Machine Learning Models for Prediction:

Application of machine leaning models such as LSTM, linear regression, decision trees, random forests, support vector machines, and neural networks may deliver expected results.

Hybrid Models:

By Combining **different** machine learning techniques such as deep learning with traditional forecasting methods can produce effective results.

Evaluation Metrics:

Performance analysis can be done with the help of common evaluation metrics for model performance, such as MAE, RMSE, and R^2 scores.

Following are the key stages in development of predictive model for solar power egenration using artificial intelligence:

- **Data Collection and Preprocessing:**

1. Historical data on solar power generation, solar irradiance, and weather variables were collected

over a year.

2. Data preprocessing involves cleaning the collected data, handling missing values, and ensuring data consistency. handling missing values and outliers.
3. Preprocessing of data is most important step to improve data quality for more effective model training and forecasting

- **Feature Engineering:**

1. The dataset may be in unstructured form hence it is required to select and transform relevant features from the data to enhance prediction accuracy into input features (solar irradiance, ambient temperature, time of day) and the target variable (solar power generation).
2. Unstructured data will be retransformed after relevant feature selection process.

- **Model Selection:**

1. The process of choosing the most appropriate forecasting model based on the nature of the data and forecasting requirements.
2. Different models like statistical methods, machine learning algorithms, or hybrid models can be considered for solar power prediction

- **Data Splitting:**

1. The dataset will be divided into a training set (70% or 80%) and a testing set (30% or 20%).

- **Model Training:**

1. In this step, model will be fed with the historical data into the selected model to allow it to learn patterns and relationships.
2. Training the model is essential to enable it to make accurate predictions based on the provided data
3. Each selected model will undergo training using the training dataset.

- **Model Evaluation:**

1. It Involves assessing the performance metrics of the trained model like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).
2. It helps in understanding the model & predictive capabilities and identifying areas for improvement in the forecasting process.

- **Results and Comparative Analysis:**

1. The comparative study of the performance of the predictive model will be carried out with existing predictive models.
2. Performance of predictive model will be carried out using evaluation metrics, such as MAE, RMSE, MAPE, and correlation coefficient.

Statistical Plan

The statistical plan describes the framework of overall workflow of research process comprising of step by step execution of data collection, analysis methods and evaluation metrics alongwith publication in the expected time frame.

Sr. No.	Task to be Done	Plan and Timeline					
		Year 1 Stage 1	Year 1 Stage 2	Year 2 Stage 1	Year 2 Stage 2	Year 3 Stage 1	Year 3 Stage 2
1	literature Survey						
2	Visit existing solar PV plant and Collection of available Real Time data						
3	Data Prepocessing and Processing Research Paper Publication n International Conference.						
4	Proposed Method Design and Simulation						
5	Testing and Validation						
6	Comparative study, Research Publication and Thesis Writing						

Limitations of the Study

Following limitations should be considered while interpreting the results of this study.

- Availability of Real Time Data as well as historical dataset for specific geographical location
- Quality of the data can have an impact on performance of model developed.
- Advanced AI models requires high computing resources and more computing time.
- Extreme weather conditions may lead to difficulty in prediction.

Expected Outcomes of Study

Based on the research objectives and methodology, the study is expected to yield the following outcomes.

- To implement and evaluate multiple machine learning models for solar power prediction.
- Identification of Best prediction model by having comparative analysis of different machine learning algorithms
- Deployment of selected prediction model for solar power prediction using weather forecasting data.
- Performance evaluation of prediction model for different data sets.
- Validation of the prediction model with real time data for reliable prediction.

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A synopsis on

A Predictive Framework for Solar Energy Generation Using Artificial Intelligence

Submitted in partial fulfillment of the requirement for the degree of PhD In

Science and Technology

(Electronics and Telecommunication Engineering)

By

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